

# AN EXPERIMENTAL ANALYSIS OF DEEP NEURAL NETWORK BASED CLASSIFIERS FOR SENTIMENT ANALYSIS TASKS

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**Abstract:** The proliferation of social media platforms and online communities has given rise to a pressing concern—the proliferation of fake profiles. We propose the development of an Artificial Neural Network system, a machine learning technique, for identifying fake profiles to determine what are the chances whether the friend request is authentic or not. The ANN architecture, including multi-layer perceptrons (MLPs) and convolutional neural networks (CNNs), is tailored to handle the complexity of social media data, accounting for non-linear relationships and high-dimensional feature spaces. The other dangers of personal data being obtained for fraudulent purposes are the presence of bots and fake profiles. Bots can be hidden or come in the form of a fake friend request on a social network site to gain access to private information. The results reveal the potential of ANNs to capture intricate behavioral and linguistic cues that distinguish authentic users from fake ones.

**Index Terms** - *Social Media, Fake Profiles, Artificial Neural Network (ANN), Machine Learning, Multi-layer Perceptrons (MLPs), Convolutional Neural*

*Networks (CNNs), Fraud Detection, Bots, Behavioral Cues, Linguistic Cues.*

**Keywords:** Sentiment classification, Neural Language Model, Machine Learning, Natural Language Processing, Textual Data, Opinion Mining, Topic Augmentation

## 1. INTRODUCTION

The massive rise in popularity of internet and its ease of access to general population has created an exponential rise in user-generated content on online platforms. People express their feelings and opinions on social media platforms through text, images and videos. Users are also able to present their views about specific products and services through interactive comments on commercial business websites and fun social interaction platforms as well. The textual content generated on these platforms has valuable insights into the commentator's opinion and feelings on the topic being discussed upon. These opinions can be better understood and effectively

through a systematic application of Natural Language Processing (NLP) techniques on texts collected. This process of identifying, extracting and categorizing information that is subjective in nature from unstructured textual content is called as Sentiment Analysis, historically also referred to as opinion mining. A system of classification of sentiment analysis can be the size of text content that we need to analyse, based on this Document, Sentence and Aspect Based Sentiment Analysis are performed. This research work focuses on sentence level sentiment analysis, which will classify a given sentence to a specific class from possible classes.

The ever-growing digital landscape has significantly impacted various aspects of society, including public health, opinion dynamics, and sentiment analysis. In a comprehensive exploration of digital data sources, Li et al. [1] conducted a systematic review of systematic reviews, shedding light on the profound implications of digital information on people's health. The study underscores the need to understand and leverage these data sources for informed decision-making in healthcare. Social media, a prominent component of the digital realm, has emerged as a valuable platform for gauging public sentiment and opinions. Gorodnichenko et al. [2] present compelling evidence of this phenomenon, drawing insights from #Brexit and #USElection. This underscores the transformative role of social media in shaping and reflecting public viewpoints. Sentiment analysis, a pivotal area within the broader context of opinion mining, has garnered significant attention. Liu [3] delves into the challenges inherent in sentiment analysis, paving the way for subsequent

research aimed at addressing these issues. Brauwerters and Frasinca [4] contribute to this discourse with a survey on aspect-based sentiment classification, providing a comprehensive overview of the state-of-the-art methodologies. The integration of advanced technologies, particularly deep learning, has revolutionized sentiment analysis. Kim [7], Er et al. [8], and Liu et al. [9] showcase the efficacy of convolutional and recurrent neural networks, as well as attention mechanisms, in enhancing text classification and sentiment analysis. These advancements underscore the pivotal role of artificial intelligence in understanding and interpreting the nuances of human sentiment expressed in digital content. As the digital era unfolds, with its vast array of data sources and analytical tools, it becomes imperative to navigate this landscape adeptly. This introduction sets the stage for a deeper exploration of the intricate interplay between digital data, sentiment analysis, and public opinion dynamics.

## 2. LITERATURE REVIEW

Sentiment analysis, a subfield of natural language processing, has garnered significant attention due to its applications in various domains. This literature survey provides a comprehensive overview of recent research, focusing on digital data sources, social media, and deep learning approaches for sentiment analysis. Li et al. [1] conducted a systematic review of systematic reviews, exploring the impact of digital data sources on people's health. The study emphasizes the importance of understanding how digital information influences public health.

Gorodnichenko et al. [2] delved into the realm of social media and public opinions, presenting evidence from the #Brexit and #USElection hashtags. The authors analyzed sentiment and its correlation with public sentiment, offering insights into the role of social media in shaping opinions. The foundational work by Liu [3] addresses the core challenges in sentiment analysis, setting the stage for subsequent research.

Brauwiers and Frasinca [4] surveyed aspect-based sentiment classification, providing a detailed exploration of the various dimensions involved in sentiment analysis. This serves as a valuable resource for understanding the nuances of sentiment expression. Deep learning has emerged as a powerful tool in sentiment analysis. Cambria et al. [5] explored new avenues in opinion mining and sentiment analysis, highlighting the potential of deep learning techniques.

Pathak et al. [6] specifically focused on the application of deep learning approaches, offering insights into their effectiveness in sentiment analysis tasks. The integration of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in sentiment analysis has been a prominent research direction. Kim [7] introduced CNNs for sentence classification, showcasing their ability to capture contextual information.

Er et al. [8] proposed an attention pooling-based CNN for sentence modeling, enhancing the model's ability to focus on relevant information. Liu et al. [9] introduced a recurrent neural network with multi-task

learning for text classification, demonstrating the versatility of RNNs in handling sentiment analysis tasks. Further advancements in the field include the work of Chen et al. [13], who improved sentiment analysis by incorporating sentence type classification using BiLSTM-CRF and CNN.

Vaswani et al. [14] introduced the transformer model, showing that attention mechanisms are crucial in natural language processing tasks. Kumar and Rastogi [15] explored attentional recurrent neural networks for sentence classification, contributing to the ongoing development of sophisticated sentiment analysis models. In the context of social media, Drus and Khalid [16] conducted a systematic literature review on sentiment analysis, emphasizing its applications. The study provides a comprehensive understanding of sentiment analysis in social media and its relevance in various domains. Additionally, the use of word embeddings, as demonstrated by Mikolov et al. [17], has been pivotal in representing semantic relationships within text data.

He et al. [18] applied a data-driven approach for university public opinion analysis, showcasing the practical applications of sentiment analysis in understanding public sentiment towards academic institutions. In conclusion, this literature survey highlights the diverse facets of sentiment analysis, ranging from its impact on health to its role in shaping public opinions through social media. The integration of deep learning techniques, including CNNs, RNNs, and attention mechanisms, has significantly advanced the field, offering more robust and accurate sentiment analysis models. The

surveyed works collectively contribute to a comprehensive understanding of sentiment analysis, providing valuable insights for researchers and practitioners in the domain.

### 3. METHODOLOGY

In literature they introduced a deep learning-based LSTM-CFR model with a convolution neural network to perform analysis of student's opinions that they express in online social media platforms. They performed the task using Chinese and English text used frequently by college going students to express themselves in online forums. Instead of relying on sentiment lexicon and machine learning models that are inherently dependent on tedious handcrafted features to make the models perform better, they used word embeddings to perform task of word vectorization. Using LSTM network and CFR jointly for the purpose of adaptive word segmentation focused on Chinese text these segmented words were then vectorized. Word vectorization through embedding and use of LSTM-CFR helps map dependencies between valuable features and sentimental opinions. The results were then passed to a deep learning CNN model which was able to classify the text.

#### Drawbacks:

1. The LSTM-CFR model combines LSTM and CNN architectures, which might be effective but lacks the integration of the Transformer. Because Transformer is a powerful attention-based model known for capturing long-range dependencies.

2. The existing work uses word embeddings for word vectorization, which is a common and effective technique. However, it does not explore or highlight any unique approaches or improvements in the word vectorization process.
3. The previous work does not provide a detailed analysis of the impact of different word embeddings on model performance. It might miss the opportunity to identify the most suitable embedding for sentiment analysis.

This work proposes a novel Transformer-BiLSTM-CNN model that gives great result on sentiment analysis task. The models proposed were analyzed with three widely popular word embeddings separately and in combined approach using all embeddings as unique channels. We combined deep neural network models such as Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Neural Network (CNN) so that integrated models complement each other with their unique architectures. The word embeddings used had profound impact in accuracy of models owing to performative changes. The best word embedding was Word2Vec giving highest accuracy in almost all implemented models, followed by GloVe. FastText embedding performed consistently worse, giving much lower accuracy than other embeddings. We also compared larger pre trained language model used in sentiment analysis task with our proposed approach.

**Benefits:**

1. The Transformer-BiLSTM-CNN model combines Transformer, BiLSTM, and CNN architectures, allowing it to potentially capture both long-range and local dependencies, making it more versatile.
2. We also uses word embeddings but performs an in-depth analysis of three popular embeddings and their impact on model accuracy, providing more insights into the role of word embeddings in sentiment analysis.
3. We thoroughly compare three-word embeddings (Word2Vec, GloVe, FastText) and identifies the best-performing embedding (Word2Vec), enabling a more informed choice for word vectorization.

- Data loading: using this module we are going to import the dataset.
- Data Preprocessing: using this module we will explore the data.
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Building the model -- CNN + Bi-LSTM –Bi-LSTM + CNN + Bi-LSTM - CNN -Transformer CNN - Transformer CNN + Bi-LSTM -LSTM - LSTM + GRU
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted display

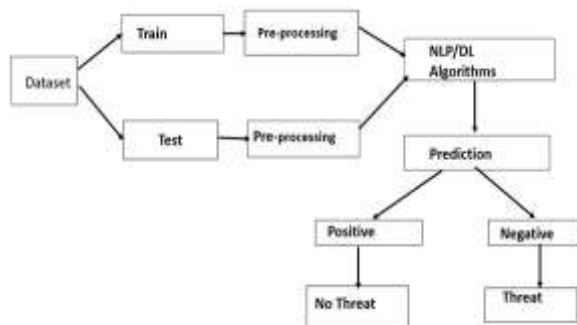


Fig 1 System Architecture

**Modules:**

The modules are:

**4. IMPLEMENTATION**

CNN + BiLSTM – A CNN BiLSTM is a hybrid bidirectional LSTM and CNN architecture. In the original formulation applied to named entity recognition, it learns both character-level and word-level features. The CNN component is used to induce the character-level features.

BiLSTM + CNN + BiLSTM – BiLSTM adds one more LSTM layer, which reverses the direction of information flow. It means that the input sequence flows backward in the additional LSTM layer, followed by aggregating the outputs from both LSTM layers in several ways, such as average, sum, multiplication, or concatenation.

CNN – A convolutional neural network (CNN or convnet) is a subset of machine learning. It is one of the various types of artificial neural networks which are used for different applications and data types.

Transformer CNN – A transformer model is a neural network that learns context and thus meaning by tracking relationships in sequential data like the words in this sentence. Transformer CNN + BiLSTM – A bidirectional LSTM (BiLSTM) layer is an RNN layer that learns bidirectional long-term dependencies between time steps of time-series or sequence data. These dependencies can be useful when you want the RNN to learn from the complete time series at each time step.

LSTM – LSTM networks are the most commonly used variation of Recurrent Neural Networks (RNNs). The critical component of the LSTM is the memory cell and the gates

### 5. EXPERIMENTAL RESULTS

#### Dataset Description:

The SST2 (Stanford Sentiment Treebank) dataset is a widely used benchmark in natural language processing (NLP) and sentiment analysis. It was introduced by Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng, and Christopher Potts as part of the Stanford NLP group.

The SST2 dataset is a subset of the original SST dataset, which was created by parsing sentences from movie reviews and annotating them with binary

sentiment labels (positive or negative). The SST2 dataset specifically focuses on binary sentiment classification, where each sentence is labeled as either positive or negative based on the overall sentiment expressed.

Here are some key characteristics of the SST2 dataset:

Size: The dataset consists of sentences extracted from movie reviews, and it is divided into a training set and a test set. The original split includes 6,920 sentences for training and 1,821 sentences for testing.

Binary Sentiment Labels: Each sentence in the SST2 dataset is labeled with a binary sentiment, indicating whether the sentiment of the sentence is positive or negative.

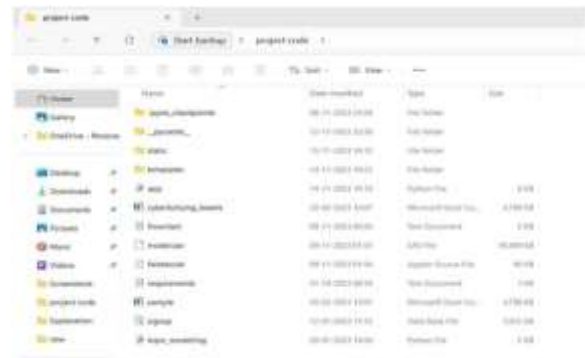


Fig 2 Files in Project Code Folder



Fig 3 Anaconda prompt



Fig 4 URL



Fig 8 Login Credentials



Fig 5 Browsing



Fig 9 Input Text Box

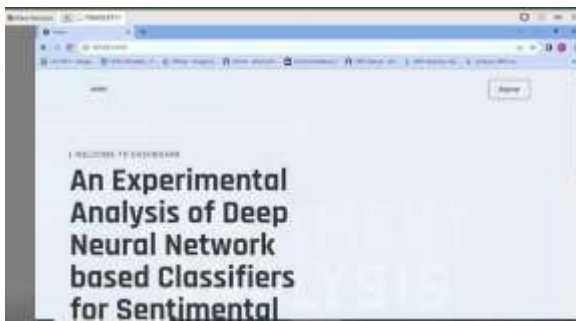


Fig 6 User home page



Fig 10 Accuracy and Precision Graphs

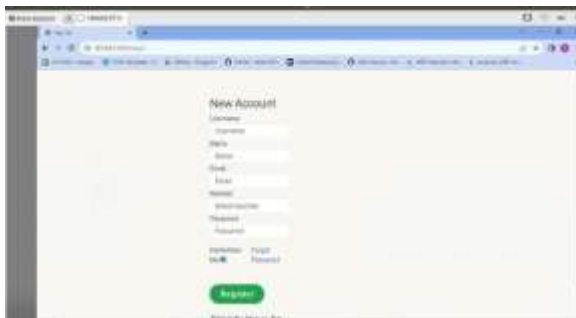


Fig 7 Signup Credentials

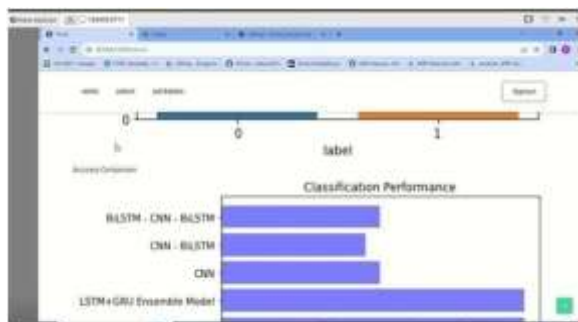


Fig 11 F1 Score comparison graph



Fig 14 Sample Output screen



Fig 12 Text Box to Enter Input



Fig 13 Sample Output screen

## 6. CONCLUSION

We have proposed Transformer-BiLSTM-CNN model with a larger number of encoder transformer layers and pre-training on a large corpus can produce better accuracy results. We have also found that the choice of word embeddings has a significant impact on the accuracy of the models, with Word2Vec performing the best among the embeddings studied. We have compared their proposed approach with larger pretrained language models such as BERT and ELMo and found that their model achieves comparable accuracy with much smaller trainable parameters. Furthermore, in context to our experimentation, the BiLSTM layer when used solely with CNN model did not perform as per our expectations, both CNN-BiLSTM and BiLSTM-CNN- BiLSTM had no visible impact on accuracy as it increased for some embedding while decreasing in other word embedding, in both cases with no high margin. The comparative analysis by using different embeddings can be beneficial to other researchers when choosing embeddings for their models. We believe that the proposed models can have a significant impact on the field of natural language

processing, particularly in the area of textual sentiment analysis.

### FUTURE ENHANCEMENTS

In advancing the experimental analysis of deep neural network-based classifiers for sentiment analysis tasks, future enhancements could focus on several key aspects. Firstly, delve into exploring innovative attention mechanisms and neural network architectures to uncover potential improvements in capturing sentiment nuances. Secondly, investigate the application of transfer learning to leverage pre-trained models, enhancing performance when labeled data is limited. Thirdly, conduct systematic hyperparameter tuning to fine-tune model configurations for optimal sentiment prediction. Additionally, consider the integration of data augmentation techniques to diversify the training dataset, promoting better generalization. Lastly, prioritize assessing model explainability and conducting cross-domain evaluations to ensure robustness across various application scenarios.

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